Flux Improvement based on Machine Learning for the CERES FluxByCldTyp Data Product

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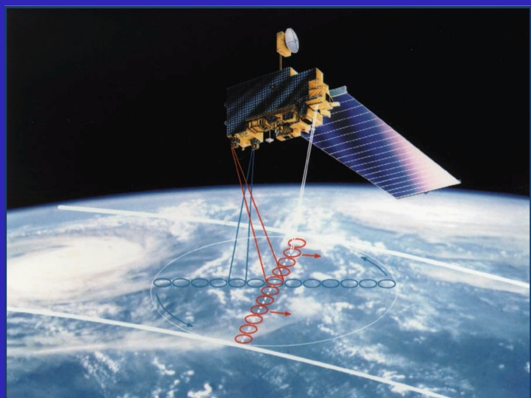
Outline

- Motivation
- CERES project and CERES FluxByCldTyp Ed4 Data Product
- SW and LW fluxes improvement based on Deep Neural Network
  - Input Data and Algorithm Setting
  - Preliminary results and validation
- Summary and future work

Motivation

The NASA CERES project provides over 22 years of observed TOA fluxes and a suite of datasets that include surface fluxes and cloud properties on different spatial and temporal scales. The Ed4 FluxByCldTyp data product is a new dataset that provide ISCCP-like cloud types and their associated radiative fluxes for climate studies which requires accurate and consistent dataset over time. As part of the effort to improve accuracy of the fluxes of FluxByCldTyp, we used machine learning technique to calculate fluxes within mixed scene satellite footprints. I will present preliminary results which show improvement over the current algorithm.

The CERES Project



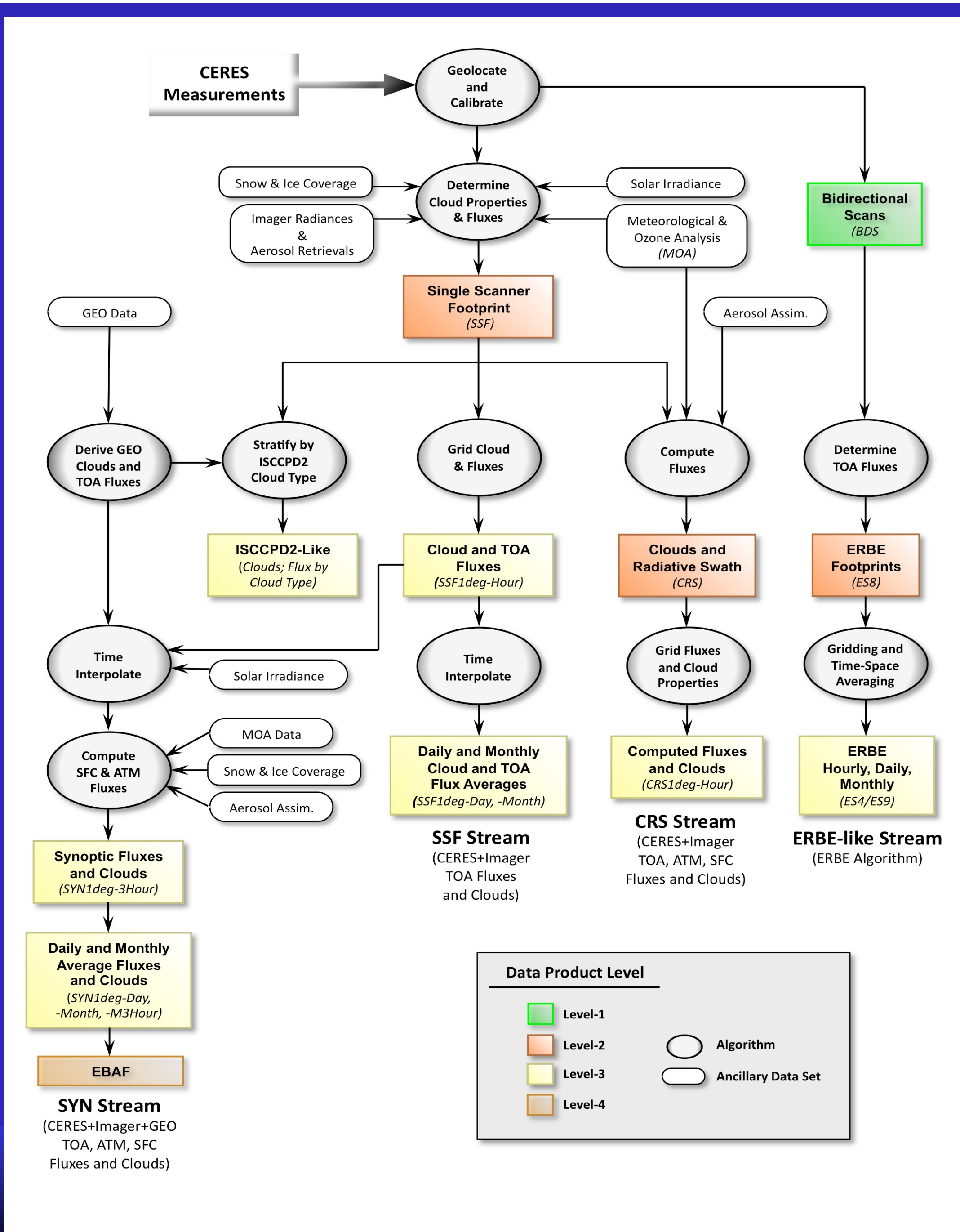
I. The Clouds and the Earth Radiant Energy System (CERES) instruments were first aboard TRMM satellite launched in December 1997 and currently on Terra, Aqua, and NPP polar orbiters.

I. CERES produces flux data products based on radiances measured in three bands.

- SW (0.3-5μm)
- IR Window (8-12μm)
- Total channel (0.3-200μm)

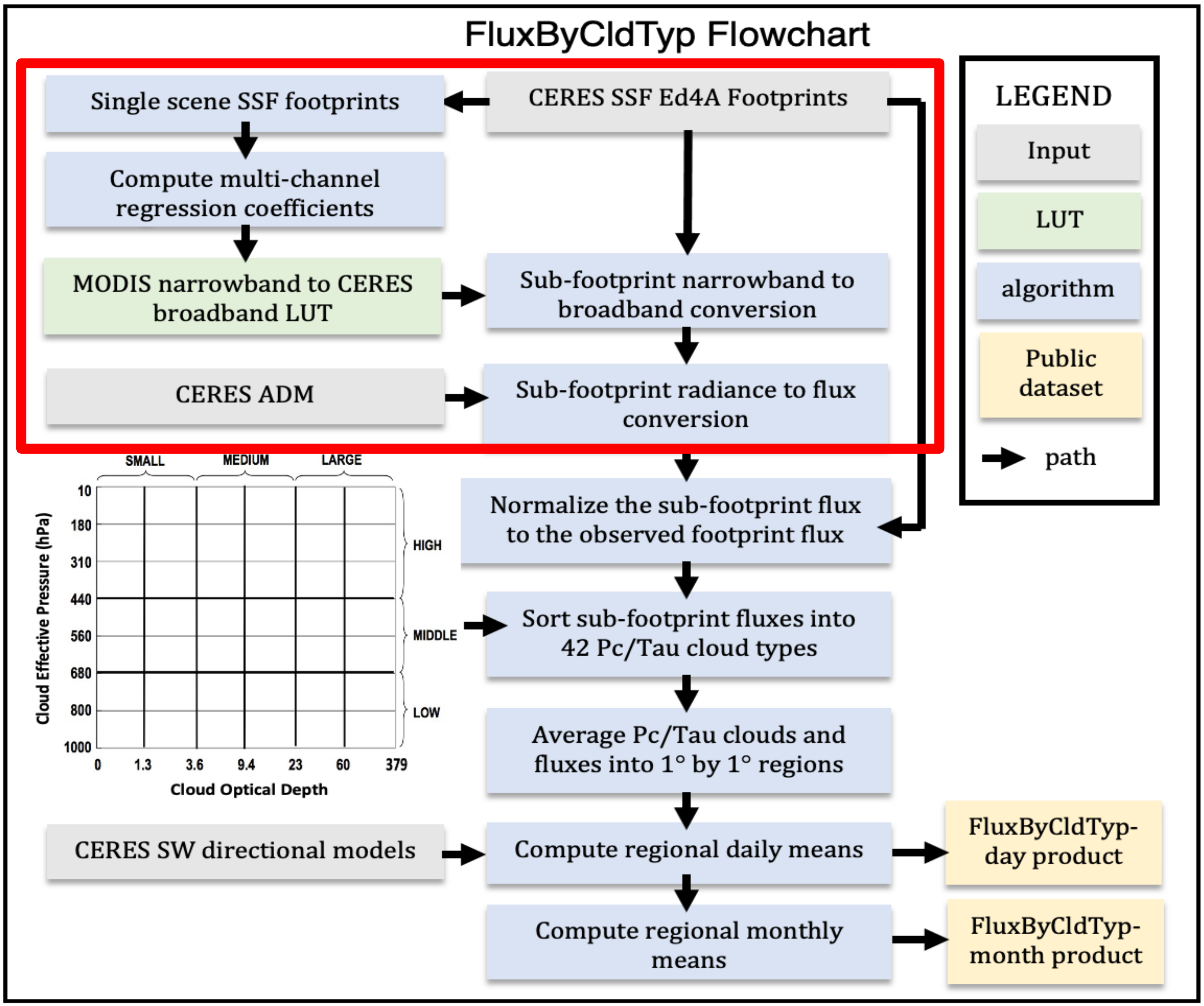
LW = Total Channel - SW

II. Cloud property are produced based on imagers like MODIS and VIIRS measurements on the same satellite.



CERES Data Product Flow Chart

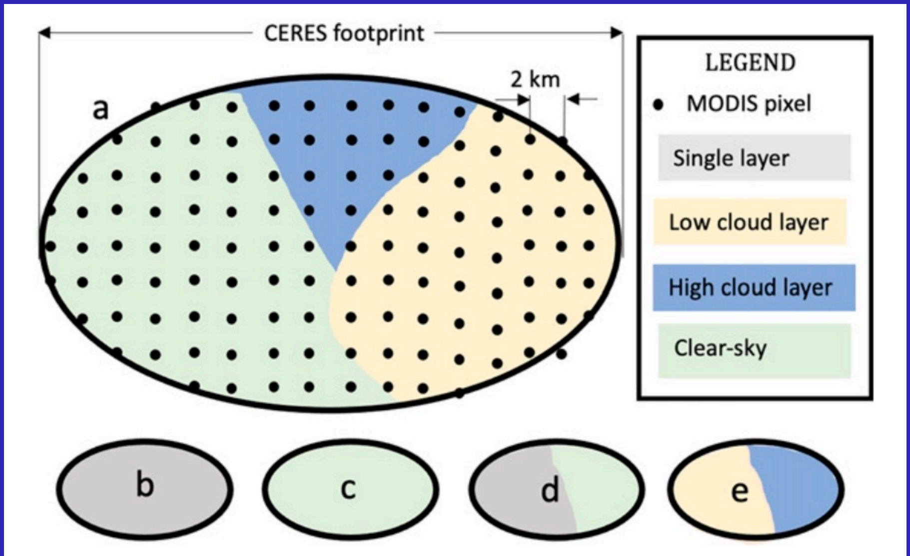
- Level 1: instantaneous footprint-level (20km nominal) ephemeris and instrument level data.
- Level 2: footprint-level (20km nominal) fluxes and cloud properties. (SSF)
- Level 3: Spatially (1° x1° lat/lon regional (zonal, global) and temporally (daily, monthly, etc.) averaged fluxes and clouds.
- Level 4: gridded, averaged fluxes where the TOA net flux has been energy balanced. (EBAF)


FluxByCldTyp Flowchart
Single scene SSF footprints
CERES SSF Ed4A Footprints
Compute multi-channel regression coefficients
MODIS narrowband to CERES broadband LUT
Sub-footprint narrowband to broadband conversion
CERES ADM
Sub-footprint radiance to flux conversion
Normalize the sub-footprint flux to the observed footprint flux
Sort sub-footprint fluxes into 42 Pc/Tau cloud types
Average Pc/Tau clouds and fluxes into 1° by 1° regions
CERES SW directional models
Compute regional daily means
Compute regional monthly means
FluxByCldTyp-day product
FluxByCldTyp-month product
LEGEND
Input
LUT
algorithm
Public dataset
path
SMALL
MEDIUM
LARGE
HIGH
MIDDLE
LOW
Cloud Effective Pressure (hPa)
10
180
310
440
560
680
800
1000
0
1.3
3.6
9.4
23
60
379
Cloud Optical Depth

SW and LW flux improvement based on Deep Neural Network (DNN)

- Input Data: CERES Ed4 SSF
  - SSF footprint structure
  - Data sampling
  - Selected variables
- DNN set-up

Input CERES SSF Data Structure



- Size: 20km nadir
- Clear, CloudLow, CloudHigh
- Parameters:
  - time, position, viewing geometry
  - surface maps, scene types
  - meteorological data
  - **radiances (Imager NB radiances and CERES BB radiances), fluxes**
  - **cloud properties**: cloud fraction, TempEff, TempTop, PressEff, PressTop, LWP, IWP, Cloud Radius, Emissivity, Optical Depth,etc.

Aim: To obtain corresponding flux for each of the three sub-footprint areas: clear, cloudLow and cloudHigh.

Data Samples

- Time: 5 Januarys (2007-2011)
- Daytime only
- Clear sky and Overcast
- Sampling: 80% train, 18% dev, 2% test

	Total Number of Samples
Overcast SW	11,273,554
Overcast LW	10,384,468
Clear sky SW	7,825,328
Clear sky LW	6,455,850

Input Variables

<table>
<tr><th></th><th colspan="2">Input Variables</th><th>Total</th></tr>
<tr><td rowspan="2">Clear</td><td rowspan="3">1. 5 MODIS Bands: 0.48, 0.65, 0.86, 11, 12 (μm)
2. 3 Angles: solar zenith, viewing zenith, relative azimuth angle
3. Longitude and latitude
4. Total precipitable water (PW)
5. Surface type (Ocean, Forests, Savannas, Grass/Crop, Dark Deserts, Bright Deserts, snow/ice)</td><td rowspan="2">T_{skin}</td><td rowspan="2">13</td></tr>
<tr></tr>
<tr><td>Over-cast</td><td></td><td>12</td></tr>
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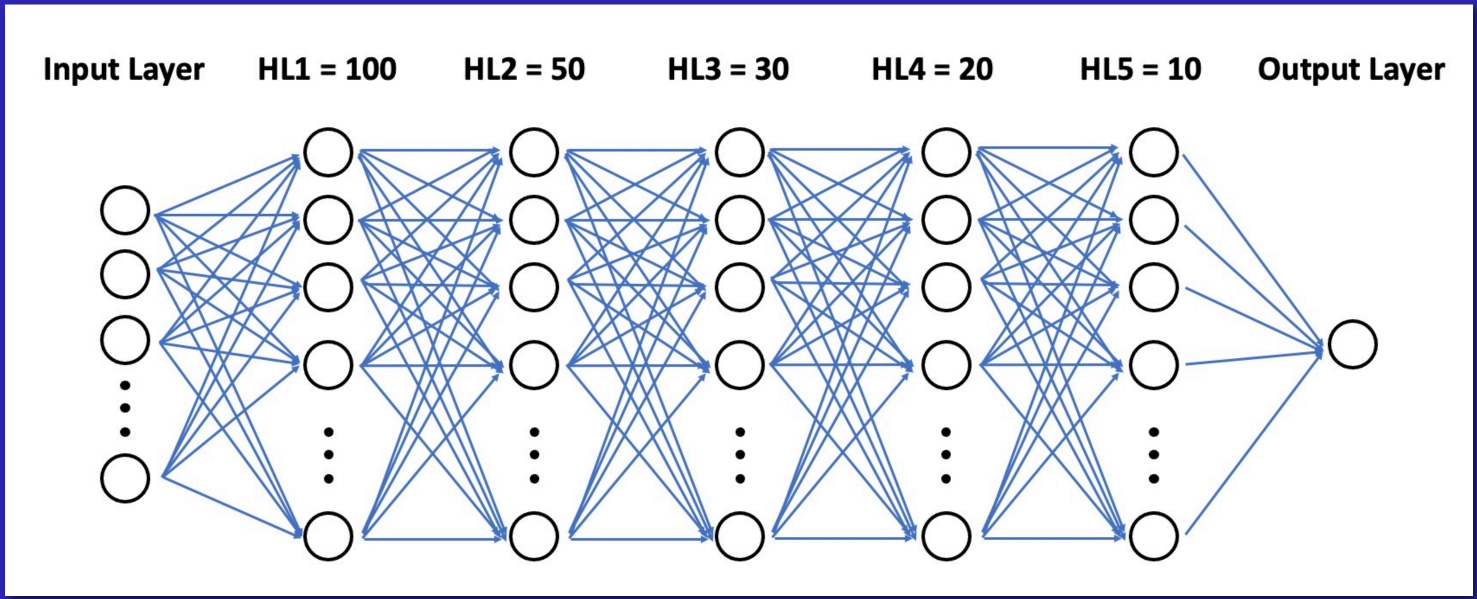
DNN Set-up



6 hidden layers with varying number of neurons

DNN set-up

- Activation Function: rectified linear unit (or ReLU):

  $$f(x) = \max(0,x)$$

- Step Decay Learning Rate:

  lr = lr0 * drop^floor(epoch / epochs_drop)
  lr0 = 0.01
  drop = 0.5
  epochs_drop = 50

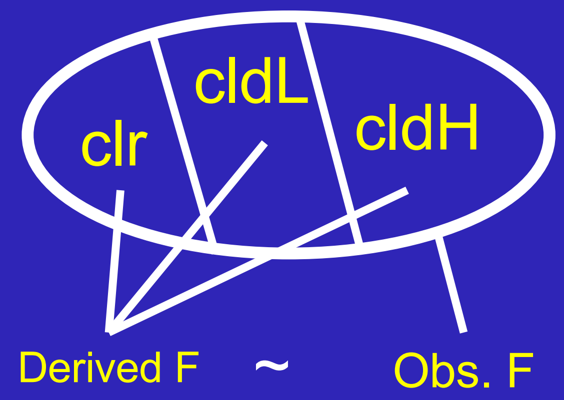
Validation: Footprint Level

For each footprint: calculated flux vs. observed flux

$$F_{fp} = f_{clr}{}^{*}F_{clr} + f_{cldL}{}^{*}F_{cldL} + f_{cldH}{}^{*}F_{cldH}$$

$f: clear/cloud\ fraction$

$F: Flux$



Perfectly, **Derived Flux == Observed Flux**

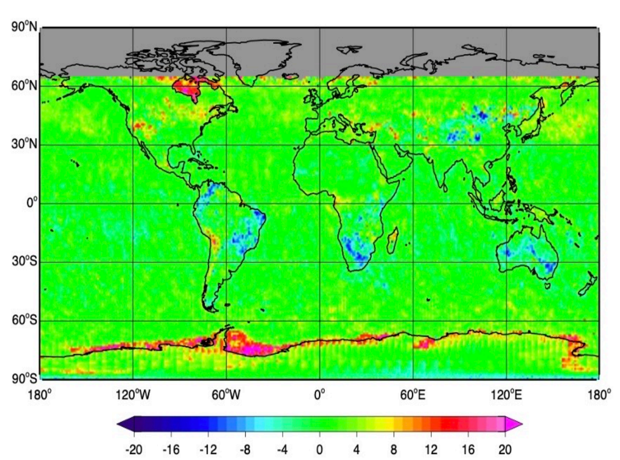
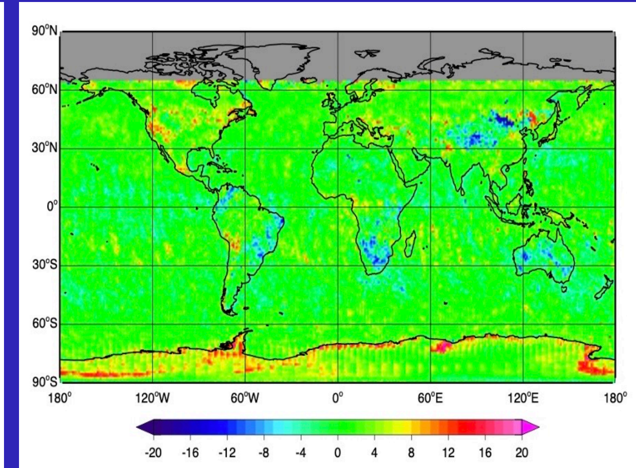
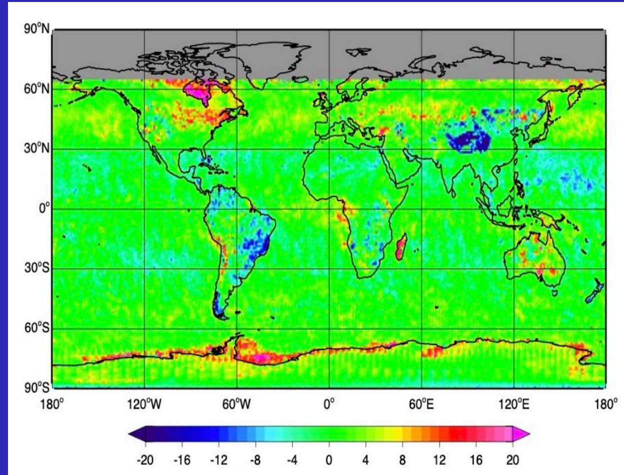
Two Methods

- Method A: Two Steps (Ed4)
  - Step 1: MODIS NB radiances -> BB radiance through DNN
  - step 2: BB Rad -> BB flux (ADM)
- Method B: One Step
  - MODIS NB radiances -> BB flux through DNN

SW Bias and RMS (Jan 2019)

Regional bias and global mean RMS

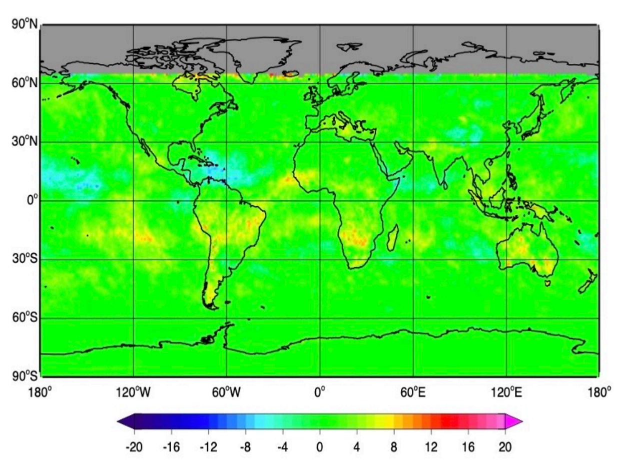
All cases are compared to the CERES observed SW flux

DNN_A	DNN_B	Ed4.1
		
Bias = 0.85 RMS = 3.21	Bias = 0.60 RMS = 3.15	Bias = 0.42 RMS = 3.99

LW Bias and RMS (Jan 2019)

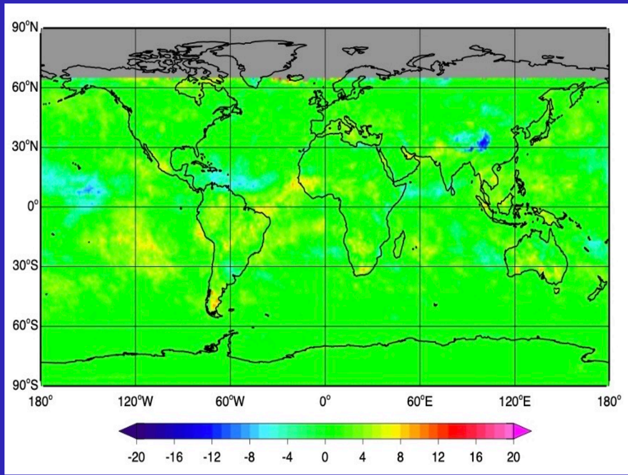
Regional bias and global mean RMS (W/m^2)
All cases are compared to the CERES observed SW flux

DNN_A



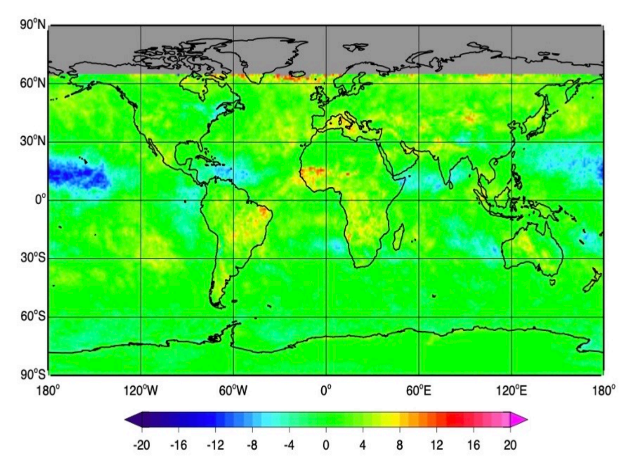
Bias = 1.14
RMS = 2.45

DNN_B



Bias = 0.97
RMS = 2.33

Ed4.1

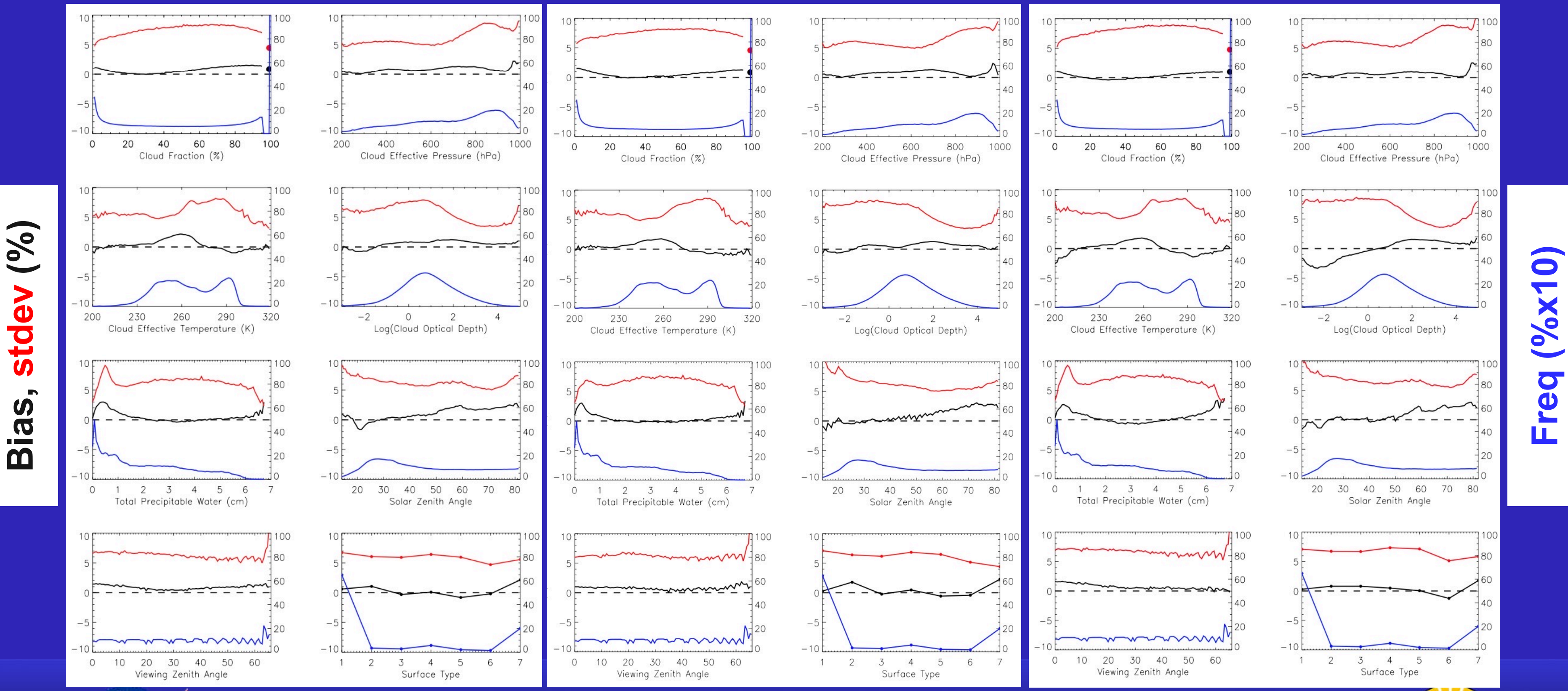


Bias = 0.70
RMS = 3.03

SW Bias and stdev (Jan 2019)

SW Bias and stdev dependency over parameters

DNN_A DNN_B Ed4.1

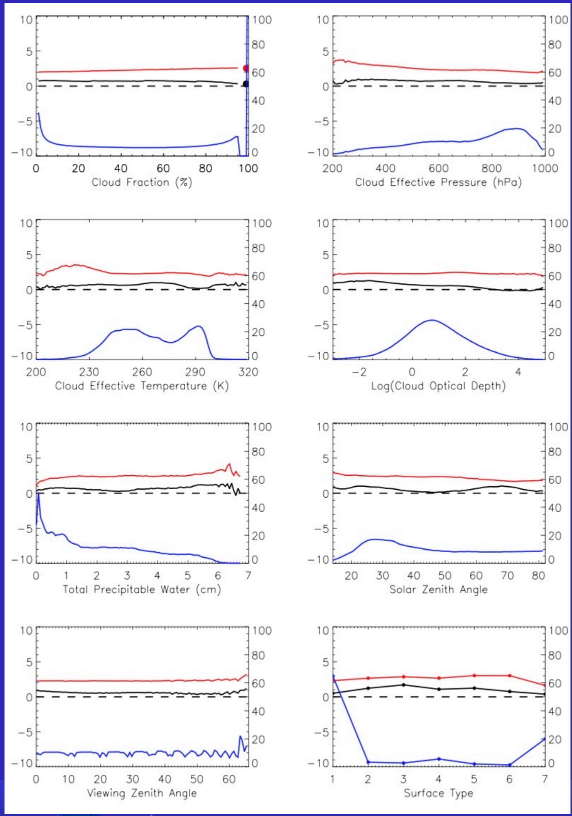


LW Bias and stdev (Jan 2019)

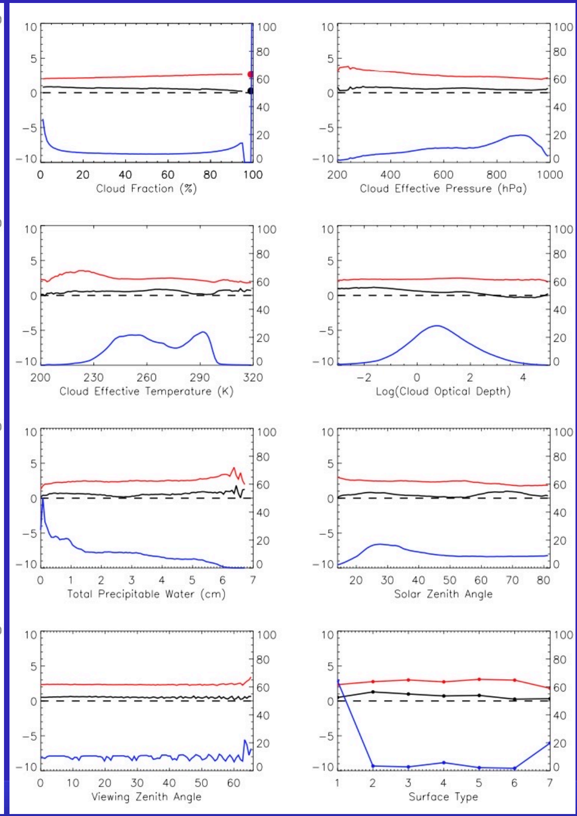
LW Bias and stdev dependency over parameters

Bias, stdev (%)

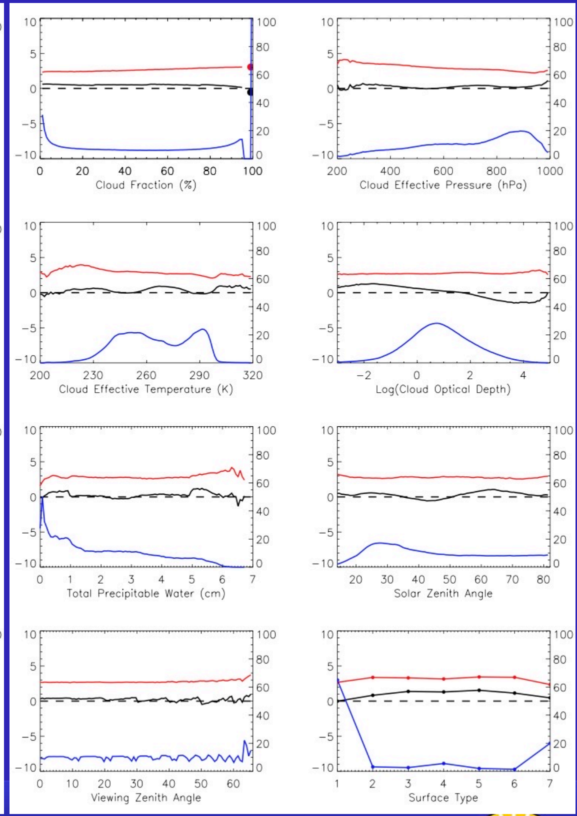
DNN_A



DNN_B



Ed4.1



Freq (%x10)

Hyperparameter Tuning

	Control	Hyper1	Hyper4	Hyper5	hyper6	hyper7
Layers And Neurons	n_h1 = 100 n_h2 = 50 n_h3 = 30 n_h4 = 20 n_h5 = 10	n_h1 = 50 n_h2 = 40 n_h3 = 30 n_h4 = 20 n_h5 = 10	n_h1 = 20 n_h2 = 20 n_h3 = 20 n_h4 = 20 n_h5 = 20	n_h1 = 10 n_h2 = 10 n_h3 = 10 n_h4 = 10 n_h5 = 10	n_h1 = 5 n_h2 = 5 n_h3 = 5 n_h4 = 5 n_h5 = 5	n_h1 = 200 n_h2 = 100 n_h3 = 60 n_h4 = 40 n_h5 = 20
SW Bias	0.598	0.369	0.509	0.629	1.953	0.414
SW RMS	3.150	3.066	3.483	3.819	4.385	3.218
LW Bias	0.965	0.981	0.853	1.062	0.916	1.043
LW RMS	2.335	2.489	2.58	2.734	3.102	2.391

Summary and Future work

- Two methods based on DNN are developed to improve fluxes in FluxByCldTyp product. They both show improvement over Ed4.1
- The two methods give about the same results and ADM is not required in that future FluxByCldTyp, thus greatly reduce code complexity
- DNN will be incorporated in to FluxByCldTyp Ed5. further improvement involves more MODIS NB channels.

Thank you!

Fore more information:
https://ceres.larc.nasa.gov/